Energy demand optimization in a seawater pumping plant by energy hybridization with solar energy and batteries.

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***Abstract*—**
This paper presents a study on the implementation of demand-side management (DSM) using model predictive control (MPC) for a seawater pumping plant in the Chilean mining industry. The study focuses on reducing energy costs, leveraging solar energy and energy storage, improving sustainability, and ensuring reliable operation. The pumping system is described, including its electrical tariff and solar resources. The demand optimization is formulated as a discrete-time model with an objective function for both real-time pricing (RTP) and maximum-demand (MD) tariffs. Results show the effectiveness of the approach in meeting the water demand of the pumping plant while reducing energy costs.

I. INTRODUCTION

The Chilean mining industry faces a scenario of lower water availability, where climate change directly influences the present and future water availability. It is projected that copper production will increase by 21.5% in 2021-2032, the same period for which it is projected that the use of continental water will decrease by 45% and seawater will increase by 167% [1]. As a result, seawater pumping plants have emerged as crucial infrastructure for mining. However, due to the long distances, height differences, and required flows, high-power pumping stations are needed to transport water to the mines, resulting in high energy costs to meet water demand. In an industry where energy demand is already on the rise due to declining mineral grades and growing concerns about its carbon footprint, there is a need to find solutions to address these energy challenges [2]. Demand-side management (DSM) is a proposed solution to narrow the energy supply and demand gap. DSM techniques include energy source substitution, self-generation, energy efficiency, and load management (LM), which involves shifting the load (LS) consumed during peak hours to off-peak hours using time-of-use (TOU) or real-time pricing (RTP) tariffs and managing peak demand under maximum-demand (MD) tariffs to reduce energy costs. DSM is implemented using a model predictive control (MPC) approach, which remains stable against disturbances and can continuously re-optimize to compensate for inaccuracies or simplifications in the models [4]. This paper presents a comprehensive study of DSM using MPC for a seawater pumping plant in the Chilean mining industry, focusing on reducing energy costs by leveraging solar energy availability and energy storage, improving sustainability, and ensuring the reliable operation of the pumping station. Our research assesses this approach's effectiveness in meeting the pumping plant's water demand while reducing energy costs.

II. SEA WATER PUMPING SYSTEMS

A. Pumping system

The mining operation transports seawater over 145 kilometers. Four pumping stations are used to transport the water, the first being the seawater intake and the others transporting the water to different processes. Pumping stations 1 and 2 are located 50 kilometers from the intake station while pumping station 3 is located 120 kilometers away. Pumping station number 3 is located near the mine, and at its outlet, there is a seawater storage pool of 60,000 cubic meters. From this reservoir, a reverse osmosis plant requires seawater to produce water for the different processes in the mine. Pumping station 3 is considered in this report due to its proximity to the mine and its direct relationship with it. This station comprises seven multistage horizontal pumps driven by induction motors connected to 3.45 kV bars with a power of 1.343 MW and a flow of 700 m3/h. The pump stations operate based on the required water demand, typically having two modes of operation utilizing either 4 or 3 pumps. The plant operates at two flow rate levels, with approximately 36% of the time using a flow rate of 2,100 m3/h and 62% of the time utilizing a flow rate of 2,800 m3/h, both contributing to meeting the water demand of the reverse osmosis plant.

B. Electrical tariff

The mining company has a contract to purchase energy at the cost of 2.5% above the marginal cost of the bus bar. Marginal costs are updated every hour and depend on the operation determined by the National Electric Coordinator and the instructions issued by the Dispatch and Control Center. The marginal cost is highly volatile, and it is common for it to remain at zero during midday hours due to the high availability of solar energy. Since the RTP tariff is not known a priori, this report considers a demand prediction using a SARIMA model prediction of the tariff to perform the optimization.

Additionally, the electric contract of the mining company includes a charge for maximum power. This charge is calculated based on the highest consumption during 15 minutes throughout the month. It is assumed that the rest of the mining operations operate at a constant power to facilitate predictive control. Therefore, the maximum demanded power incurs an additional cost for maximum demand at the end of the month.

C. Solar resources

To determine the solar potential of the plant, we considered the available solar resources based on its geographical coordinates. The plant is located at Latitude: 22.98°S, Longitude: 69.15°W, Altitude: 2113 m. Solar data was sourced from the Global Solar Atlas, a resource provided by Solargis and owned by the World Bank Group.

III. Demand optimization

For the models used in this report, a general formulation is considered with M pumps and N control horizons. The plant is formulated as a discrete-time model with a sampling time represented by the variable Δ.

A. Objective function

The objective functions I_p and I_{md} that correspond to the RTP and MD tariff can be stated as following.

$$I_p = \sum_{i=1}^{N} E_{pi} p_i \tag{1}$$

$$I_{md} = p_{md} \max \left\{ \frac{E_{pi}}{\Delta}, (1 \leq i \leq N) \right\} \tag{2}$$

Where E_{pi} and p_i denote the energy purchased and its corresponding price at time instant i, respectively. The validity of Equation (2) relies on the selection of Δ as an integer multiple of the maximum demand period. However, since the definition of the maximum demand period in (2) is nonlinear, an additional variable z_n and extra constraints (4) are introduced to transform the nonlinear objective function in into a linear one.

$$I_{md} = p_{md} z_n \tag{3}$$

$$\frac{E_{pi}}{\Delta} - z_n \leq 0, \quad (1 \leq i \leq N) \tag{4}$$

B. Operational constraints

The amount of energy purchased at each time instant is determined by the energy balance equation specific to the given problem. Depending on available energy sources, four different variations of the energy balance equation can be defined. These variations can be used to solve optimization problems related to different scenarios, such as optimal pump switching (5), optimal utilization of solar resources (6), optimal utilization of battery (7), and optimal utilization of both solar energy and batteries (8).

$$E_{pi} + \sum_{m=1}^{M} u_{mi} P_m \Delta = 0, \quad (1 \leq i \leq N) \tag{5}$$

$$E_{pi} + E_{si} + \sum_{m=1}^{M} u_{mi} P_m \Delta = 0, \quad (1 \leq i \leq N) \tag{6}$$

$$E_{pi} + E_{di} + \frac{E_{ci}}{n_{roundtrip}} + \sum_{m=1}^{M} u_{mi} P_m \Delta = 0, \quad (1 \leq i \leq N) \tag{7}$$

$$E_{pi} + E_{si} + E_{di} + \frac{E_{ci}}{n_{roundtrip}} + \sum_{m=1}^{M} u_{mi} P_m \Delta = 0, \ (1 \leq i \leq N) \tag{8}$$

Where the variables E_{si}, E_{di}, and E_{ci} represent the solar energy utilized, the energy discharged from the batteries, and the energy used to charge the batteries, respectively, at a given time instant i. The variable u_{mi} represents the binary on/off status of the pump m at the instant i. P_m is the power of the pump m and $n_{roundtrip}$ is the battery round-trip efficiency.

Further restrictions must be implemented to ensure that the reservoir levels stays withing allowed operational bounds (10). An additional constraint to keep the initial and final levels constant is implemented by (11). Where w_i are the withdrawals from the reservoir at each instant, q_m is the flow rate of the pump m,

$$H_{i+1} = H_i + \sum_{m=1}^{M} u_{mi} q_m \Delta - w_i \tag{9}$$

$$H_{lb} \leq H_i \leq H_{ub}, \quad (1 \leq i \leq N) \tag{10}$$

$$\sum_{i=1}^{N} \sum_{m=1}^{M} u_{mi} q_m \Delta \geq \sum_{i=1}^{N} w_i \tag{11}$$

To model solar availability, hourly solar profiles are used considering an installed capacity and an scaling variable PV_{scale} to simulate different capacities of PV array installed. The equation (13) bounds the utilized solar energy variable to the maximum solar energy available at each instant.

$$S = PV_{scale} S_{month} \tag{12}$$

$$0 \leq E_{si} \leq S_i, \quad (1 \leq i \leq N) \tag{13}$$

To model the behavior of batteries, a general formulation is considered, which takes into account a certain number of B_n batteries, with a maximum power of P_{Bmax} and a capacity of B_c. To ensure accurate modeling, several constraints must be specified. Firstly, mutual exclusivity between charging and discharging needs to be ensured by the use of additional binary decisions variables (14). Coupling operational constraints between binary and continuous state/energy variables (15), (16). Modeling the battery's state of charge (17), and enforcing bounds on the state of charge (18). Additionally, a constraint is incorporated to ensure that the battery state of charge remains the same at the start and end of the simulation (19).

$$0 \leq u_{di} + u_{ci} \leq 1, \quad (1 \leq i \leq N) \tag{14}$$

$$0 \leq u_{ci} B_n P_{Bmax} \Delta - E_{ci}, \quad (1 \leq i \leq N) \tag{15}$$

$$0 \leq u_{di} B_n P_{Bmax} \Delta - E_{di}, \quad (1 \leq i \leq N) \tag{16}$$

$$B_{i+1} = B_i - E_{di} + E_{ci} \tag{17}$$

$$B_n B_c B_{lb} \leq B_i \leq B_n B_c B_{ub}, \quad (1 \leq i \leq N) \tag{18}$$

$$\sum_{i=1}^{N} [E_{ci} - E_{di}] \geq 0 \tag{19}$$

The equations (15) and (16) not only couple the binary and continuous variables but also impose an implicit limit on the continuous energy used for charging or discharging the battery, which cannot exceed the maximum power of the battery. In the specific case of a battery with discrete power outputs, such as those used in this study, the equations (21) and (20) offer an alternative by allowing the replacement of continuous energy variables with discrete variables $\hat{E}_{di}$ and $\hat{E}_{ci}$, along with the introduction of the power step size $B_{powerstep}$.

$$E_{di} => \hat{E}_{di} B_{powerstep} \Delta \tag{20}$$

$$E_{ci} => \hat{E}_{ci} B_{powerstep} \Delta \tag{21}$$

IV. Simulation results

The simulations were conducted as an open-loop optimization with a 1-hour control interval for a two-day operation. The RTP tariff was the prediction for the first two days of the third week of September 2022, with a maximum demand tariff of 12.5657 USD/kW-month. The reservoir operational bounds are set between 15.000 and 45.000 m3. The daily water demand is 60,900 m3, following the same profile specified as pump operation in II-A. Solar availability was evaluated using an installed capacity of 5,000 kWp and hourly solar profiles for September. Energy storage was assessed using four Megapack "2-hour" batteries, each with a total capacity of up to 2.529 MWh, maximum power of 1.264 MW, and incrementally adjustable by 0.843 MW, with a round-trip efficiency of 87%. The models are of the type MILP and are optimized using a high-performance optimizer called HiGHS. It was implemented with its interfaces for Python through the "SciPy" library. The operational costs for each model are summarized in Table I. The figure shown in 1 illustrates the model operation that integrates solar availability and energy storage. Notably, the batteries exhibit a charging behavior characterized by long ramps and low power levels. This charging strategy is designed to make the most of surplus solar energy and reduce maximum demand costs. In addition, the model shows the purchase of energy in the shape of blocks during times of low cost, with battery power being utilized to meet energy demands during high-price hours. Overall, the optimized model represents an excellent example of how solar energy and energy storage can be integrated to achieve a high level of coordination and efficiency in energy usage.

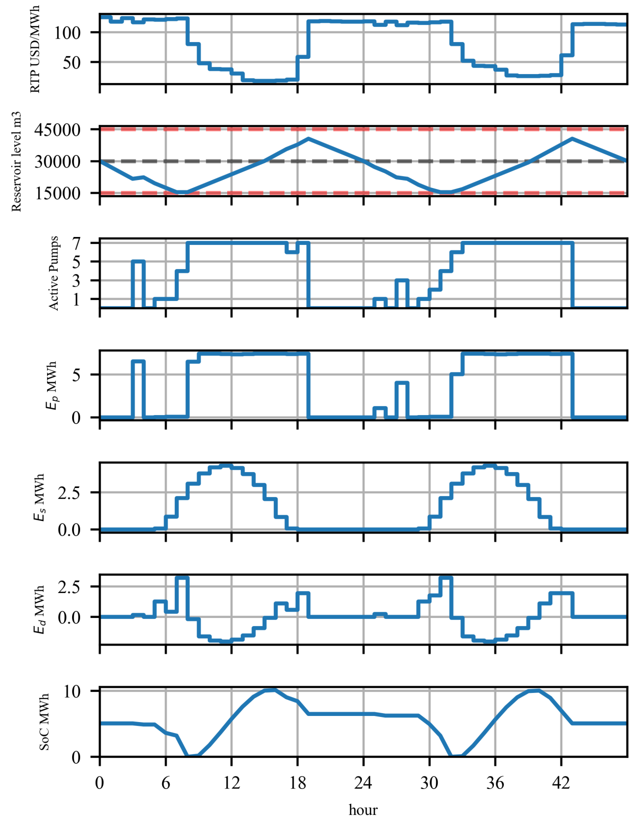

Fig. 1. RTP tariff SARIMA prediction, reservoir level, number of active pumps, energy purchased, solar energy used, energy supplied by the battery, battery state of charge.

TABLE I
Summary

	USD			MWh		
Model	$I_p + I_{md}$	I_p	I_{md}	$\|E_p\|_1$	$\|E_s\|_1$	$\|E_d\|_1$
Normal	24.054	19.554	4.500	233,7		
Optimal	19.200	11.325	7.875	233,7		
Solar	15.411	9.786	5.625	169,4	64,3	
Battery	18.818	10.050	8.768	236,4		18,3
Solar+Battery	13.816	7.561	6.255	172,4	64,3	20,1

V. Conclusions and further work

This work has proposed a DSM strategy for a seawater pumping system delivering fresh water to mining operations. The strategy considers energy storage and renewable energy sources available in northern Chile. Simulation results show that the proposed models work well for the optimal operation of a real plant. All models generated excellent results in reducing energy consumption and maximum demand costs. Using existing infrastructure for load displacement, a simple model to optimize pump operation significantly decreased operating costs. A solar energy model reduced purchased energy costs and maximum demand costs by using higher solar irradiation hours to activate pumps. A battery model bought low-cost energy and supplied high-cost demand. Combining solar energy and batteries showed coordinated functionality and complemented each other with solar surpluses for maximum demand tariffs.

Further work could involve optimizing the system through optimal sizing and global optimization. Optimal sizing would determine the most efficient sizes for system components with economic investment analysis. Global optimization would simultaneously optimize a set of pumping stations, using previous studies to find the best overall system design.

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